

Beyond Nadel's Paradox. A computational approach to structural and cultural dimensions of social cohesion

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ABSTRACT

Nadel's Paradox states that it is not possible to take into account simultaneously cultural and relational dimensions of social structure. By means of a simple computational model, the authors explore a dynamic perspective of the concept of social cohesion that enables the integration of both structural and cultural dimensions in the same analysis. The design of the model reproduces a causal path from the level of conflict suffered by a population to variations on its social cohesiveness, observed both from a structural and cognitive viewpoint. Submitted to sudden variations on its environmental conflict level, the model is able to reproduce certain characteristics previously observed in real populations under situations of emergency or crisis.

Subject headings: social cohesion, dynamic analysis, social structure, conflict, social networks

1. Introduction

Paul Dimaggio (Dimaggio 1992) reminds us the Nadel’s Paradox, who followed the distinction done for Radcliffe-Brown (Radcliffe-Brown 1940) and the British structural-functionalist school between culture and structure:

This is Nadel’s Paradox: A satisfactory approach to social structure requires simultaneous attention to both cultural and relational aspects of role-related behavior. Yet cultural aspects are qualitative and particular, pushing researchers toward taxonomic specificity, whereas concrete social relations lend themselves to analysis by formal and highly abstract methods. ((Dimaggio 1992):119-120).

Nadel (Nadel 1957) was interested in describing social structure as a web of roles, which were composed both by a pattern of relationships with other roles as by a cultural content observable in behavior. While getting knowledge of the pattern of relationships implied formal operations and allowed consequently a strong operationalization, the description of variability of role’s cultural content led to broad typologies and implied a weak operationalization. At the same time, the structural patterns could be aggregated in greater structures while cultural based typologies only could be considered substantively. This weak operationalization is common in Social Sciences: ‘Mind’ in the psychological literature, ‘culture’ in anthropology or ‘wealth’ in economics, for instance, they all share a vague definition, due both to the central role they play in their disciplines, and to a long and abundant literary history.

This paradox is real, and it represents the different traditions in Social Sciences and Humanities among other dualities, as the pairs qualitative-quantitative and structure-agency, for instance. From our point of view, social networks perspective allows overcoming some of those dualities for its capacity for being situated among the *macro*, historical and institutional level, and the *micro*, the individual and biographic agency, the *mesolevel*.

Moreover, a *dynamic* perspective of social networks allows taking into account social norms culturally determined *and* social patterns of relationship among individuals and groups. For illustrating this point we will concentrated in *social cohesion*, especially for the role played for it in the emergency of social movements in moments of crisis.

Social cohesion is also a concept with a long history and multiple definitions (Kearns & Forrest 2000; Friedkin 2004). Needless to say, social cohesion has been an issue under study in sociology since its modern foundations (Durkheim 1956) , affecting many related issues such as community structure (Forrest & Kearns 2001) or population health (Wilkinson 1996; Kawachi & Kennedy 1997) and, as a consequence, an attempt to develop a theory of social cohesion is confronted with partial definitions of it, complex literature from different sociological schools or unsuited approaches (Friedkin 2004). From a theoretical point of view, for instance, the concept is diffuse because of the difficulties in isolating its meaning, which overlaps several other core concepts such as solidarity, inclusion or integration. As an example, Kearns and Forrest (Kearns & Forrest 2000) distinguish as much as five different facets of social cohesion (which they name *constituent dimensions*), including common culture, solidarity, networks and social capital, and territorial belonging and identity. These manifold features entail intrinsic methodological difficulties, since they include cognitive, social, structural and spatial dimensions. Moreover, from the methodological standpoint it is not clear whether social cohesion is to be understood as a cause (or independent variable) of other phenomena, such as economic performance (Wolfe 2002) or well-being (Wilkinson 1996), or as a consequence (dependent variable) from other phenomena, i.e. community dynamics (Putnam 1993) or economic restructuring (Polanyi 1944).

The need of a certain degree of consensus around the definition of cohesiveness is central to Social Sciences, since it is related to many phenomena of interest, such as community con-

ceptualization (Wellman & Leighton 1979; Wellman et al. 1996), social exclusion and integration (Room 1995) or the concept of embeddedness (Granovetter 1985; Granovetter 1992), mainly relevant in economic sociology.

Returning to the first paragraphs, a common strategy to short-circuit such millstones in social sciences is operationalization, i.e. defining methodological and quantification paths towards the fixation of the concept. For instance, such scheme lies at the kernel of cognitive psychology, which has turned the ethereal cartesian 'mind' into an information-processing construct.

Beyond its theoretical conceptualization, attempts to operationalize cohesion have appeared, mainly from a social networks approach (Wasserman & Faust 1994; Moody & White 2003), which is specially well-suited for the mathematical treatment of social interaction. One approach in this line which has received a significative attention is *Group structural cohesion*. It applies both to small sets and larger scales, and is defined as "*the minimum number of actors who, if removed from the group, would disconnect the group*" (Moody & White 2003). Notice that, as the authors themselves highlight, such definition's scope is limited to relational (node connectivity) aspects, and fails to capture other relevant dimensions of cohesion and related concepts like *solidarity* and *embeddedness*.

Thus, operationalization is not a final solution, but a means to re-locate and focus the study of the fundamental issues. Accordingly, the aim of this paper is to broaden Moody and White's influential proposal on structural cohesion, by integrating a cognitive, cultural component to the already-existing structural one in dynamical environments.

In particular, we will argue that social cohesion is a process through time, genuinely

a dynamical concept. Given a network topology at a moment in time, the measure of structural cohesion fails to grasp other dimensions of the concept, while an evolutive treatment of it allows the inclusion of the cultural and cognitive elements, which may be stated as follows (Carley 1991): (1) Individuals are continuously engaged in acquiring and communicating information; (2) what individuals know influences their choices of interaction partners; and (3) an individual’s behavior is a function of his or her current knowledge.

To make such an evolutive treatment, we have developed a computational model. As far as we know, previous works addressing this topic by means of this sort of tools, have fulfilled the requirements above only partially. One significant example is (Marsili et al. 2004), where authors analyze the structural cohesion of a population of individuals (in terms of its network’s resilience to a dynamic, uncertain, scenario). The computational model presented there, captures the interplay between information and network dynamics (first two points in the list above), but does not include the cultural component we are stressing here (third requirement).

In the remainder of this introduction, we give a brief discussion of the main components of our hypothesis, which include a short comment on the cohesion concept based on the analysis of three bibliographic examples, and some sociological background considered for the design of the model presented in the paper. The second subsection is devoted to a detailed description of the model’s main components. Finally, our results are summarized in the third part, along with evidence from historical sociology that provide empirical support to our claims.

1.1. Empirical motivation

In order to outline the purpose of this work, we offer three examples taken from sociology (Gould 1991), economics (Stark & Vedres 2006) and anthropology (Murphy 1957) that may illustrate it.

Gould’s paper (Gould 1991) analyzes insurgent activity during the Paris Commune in 1871, which sprung after a mixture of political, economic and war crises. In this paper, as in later works (Gould 1995; Gould 1993) Gould settles, by means of data analysis, that organizational networks and pre-existing informal networks interacted in the mobilization process. As Gould points out, mobilization does not just depend on existing social ties; it also creates them. Although members of a protest organization may have joined because of a pre-existing social tie to an activist, they also form new social relations while participating in collective protest.

Stark’s work (Stark & Vedres 2006) on economic dynamics covers a time interval centered on the transition years (from a communist regime towards an open market economy) in Hungary, which were characterized by political and economic discontentment. Stark analyzes cohesive processes at the economic level by means of large data sets, studying the formation (and dissolution) of clusters of firms. Examining Hungary’s political history in that period of time and Stark’s economic survey, it is possible to observe a certain correlation between both processes. In the early 90’s, economic cohesion appears to evolve as a delayed result of civil unrest. Stark’s work will be more thoroughly developed in section 3.

Finally, warfare patterns are the main concern in Murphy’s study (Murphy 1957) of

a Brazilian Indian group, the Mundurucú. Mostly in the 19th century, the Mundurucú participated in many raids, mainly for cultural reasons, secondary as a mercenary service for the Brazilians. Besides its anthropological interest, the remarkable fact is the organizational aspects of warfare within this Amazonian culture. The Mundurucú, although a cultural unity, was settled in several apart villages, spread along the upper Tapajs River. However, the setup of war parties evidenced a strong relationship among these communities, otherwise unobservable: intercommunity cooperation in warfare was facilitated by cross-cutting ties of residential affinity and affiliation by descent. For example, any Mundurucú man was a member of his own village, in most cases a native of another village, and in several instances a former resident of the village of a divorced wife; he was also linked by ties of patrilineal descent to all the villages in which members of his clan resided. Therefore, he was not involved in any cohesive and localized lineage unit. The kinship structure imposed no strict boundaries upon the local group and the male social world was widely distributed.

After these short resumes, we can point out some remarkable facts observed in the three cases despite corresponding to different scenarios and scholar approaches:

- All the approaches here presented are focused on *processes*, rather than static *situations*, they consider different kind of events through time.
- Some type of conflict is present and central to each work. Notice that *conflict* is here understood in a broad manner, and therefore it might sometimes imply violence, sometimes passive resistance, etc.
- The structural characteristics of the system after the conflict occurs is different from the structural characteristics before it. Some of the work presented settles this fact explicitly, like Gould's, while the data presented in others, like Stark's, state it implicitly.

Underlying all these formal resemblances rest the main ideas that constitute our proposal’s framework. Those ideas, that we have tried to capture in our model’s design, are listed in the following.

Taking structural and cognitive components of cohesion into account is (only) possible through dynamic observation of a system. It can be said that while structural cohesion is observable in static environments, cohesion growth depends on mobilization and recruitment that take place through *changes* at the individual level (Snow et al. 1986).

Explaining dynamical behavior demands to elucidate how macro, meso and micro variables interact during conflict, and how they affect cohesion. Social movement behaves in a regular pattern; from the institutional (macro) level to the cognitive, psychologic (micro) sphere through the (meso) level of networks and vice versa (Coleman 1990). This interaction at the meso level is complex and it is constituted both for processes of selection on the part of individual and influence by groups (Snijders et al. 2006).

In other words, a mobilization begins with a mobilization potential which depends both on macrostructural factors such as demographic, economic or ideological variables and individuals predispositions and social networks structures in which they are embedded, who, in turn, change their connectivity thus affecting social groups’ structure and the macrostructural framework.

It is possible, considering the previous items, to observe *covert cohesion*, i.e. beyond existing ties among agents, conflict activates potential, previously nonexistent links, which effectively cause cohesion growth. Conflict itself is not a direct cause of the

observable changes in structural cohesion, but a link in a causal chain; instead, clash affects information exchange among agents (consciousness-raising, (Hirsch 1990)), triggers possible out-group ties between subjects and by doing so uncovers an existing cohesion which depends both on structure and cognitive level. Covert cohesion, then, takes it form at the cognitive level, and is expressed at the group level by means of increasing structural cohesion.

The computational model described in the next subsection assumes the mentioned causal relationship, therefore bestowing structural cohesion with the cognitive component, being then an appropriate implementation of the described hypothesis.

1.2. Modelling of Social Cohesion: Backgrounds

The preceding examples illustrate that there are underlying mechanisms which allow the emergence of cohesion. However, such approach is mainly qualitative, whereas this work is concerned about simulation and quantification of such underlying mechanisms. The model we introduce is meant to implement plausible dynamic behavior, attending the mainstream sociological theories on interaction among agents.

Although there is a growing literature in dynamic models of networks analysis (Wasserman & Robins 2005; Snijders 2005; Marsili et al. 2004) and other for simplification purposes, the description of the model will follow Carley’s discussion about group stability. Following Carley’s theory (Carley 1991), realistic social modelling ought to incorporate (1) a structured model of information, (2) a model of information forgetting, (3) institutional or environmental limits on interaction or forced interaction, (4) a model of population dynamics, or (5) a model of information discovery.

Regarding social dynamics (4 in Carley’s list), we have followed Lazer’s directions on coevolutionary systems (Lazer 2001). According to him, social change is not to be understood *solely* in terms of the context, nor *solely* on individual choices. On the contrary, an appropriate account for social dynamics is to be found somewhere within those two extremes: individuals’ choices are molded by the network, and individuals’ behaviour actively affects the network as a whole. In order to provide for such requirement, the model’s dynamic is driven by a co-evolution model proposed by Holme and Newman in (Holme & Newman 2006), which assumes Lazer’s premises on coevolution, i.e. the system evolves in a twofold way: individuals become likeminded because they are connected via the network (change is induced by the structure) or they form network connections because they are like-minded (structure undergoes change). It does so by either redefining the connectivity of the population of agents or by changing their positioning in the social space.

However, since one of the major elements of integration is the extent to which various members interact with one another, modeling social cohesion demands not only a dynamical characterization, but also needs to include the notion of social distance (1 in Carley’s list). Following Blau (Blau 1977; Blau & Schwartz 1984) and Fararo and Skvoretz (Fararo & Skvoretz 1987) we can fulfill such need. According to them, interaction among agents depends on the number of dimensions that people have in common. Unifying Granovetter (Granovetter 1973), Blau, Fararo and Skvoretz link interaction and similarity directly on social dimensions, positing that social associations are more prevalent between persons in proximate than those in distant social positions. Such a principle can be translated in probabilistic terms, and thus become part of our computational model.

Accordingly, along with dynamic behaviour stated above, the system comprises social distance treatment. To do so, the model includes a definition of the linkage probability between two individuals, proposed in (Boguna et al. 2004), that is based on the social distance between them in a social space of a certain dimension. As in Fararo and Skvoretz, this specification weights all dimensions equally.

As for item 3 in Carley’s list, the equation defining linkage probability includes a parameter that expresses the degree of conflict. This parameter is named *social temperature*, since it allows the model to simulate situations of political disorder, warfare or large demographic changes (high social temperature).

There is still another important feature of the model that needs some development, which corresponds to item 2. In the search for a realistic treatment of information exchange among subjects, the system includes a external universal parameter (i.e. it applies to all agents and is independent of the system state), which deviates or modifies their current knowledge in a different way for each member of the population. As it is explained below, we name this parameter *social noise*.

2. COHESION ANALYSIS THROUGH A COEVOLUTIVE MODEL

In the previous chapter, we have developed the main guidelines of our model’s design from the analysis of three works in the literature related, in some sense, to social cohesion. In this chapter, we make a complete description of the model, paying especial attention to concepts introduced above such as *social temperature* and *social noise*.

2.1. Complete description of the model

We consider a population of N agents, connected through a variable number of undirected (bidirectional) links. Each agent i presents a h_i value, corresponding to his location in a continuous lineal social space of size L (proportional to N). Taking into account the explanations of the previous chapter, h_i could be seen as an opinion or positioning of individual i in relation to a certain topic (related to religion or politics, for instance).

Initially the h values of all agents are assigned randomly, following a uniform distribution along the lineal social space. Besides, the initial arrangement of the edges correspond to a topology with the same structural properties than real social networks (like large clustering coefficient and positive degree correlations, for instance). To construct such a scenario, we use a class of models proposed in (Boguna et al. 2004), that are able to grow up networks with social-like macroscopical (global) properties from a microscopical (individual) definition of the linkage probability between two agents. The key element of that definition, is the social distance between the two individuals in a social space of a certain dimension $d_{\mathcal{H}} \geq 1$. Since our social space is lineal, here we use a simplified expression of the linkage probability with $d_{\mathcal{H}} = 1$:

$$r(h_i, h_j) = \frac{1}{1 + [b^{-1}d(h_i, h_j)]^\alpha} \quad (1)$$

Where $d(h_i, h_j)$ is the social distance, b a parameter controlling the length scale of the lineal social space, and α quantifies the homophily, that is, the level of restrictiveness of an

individual to interact with others in function of their social affinity (McPherson *et al.* 2001). So, given a certain social distance between two agents, different combinations of b and α values lead to different link probabilities, in such a way that the higher the b and the lower the homophily, the larger the probability of connection.

As said in the previous chapter, the model evolves from the initial scenario in a twofold way, by redefining both the topology of the network and the positioning of the population of agents in the social space. Based on a co-evolution model proposed by Holme and Newman in (Holme & Newman 2006), the two main mechanisms that boost this co-evolution process are the rewiring of links and the imitation of h values among agents. Additionally, we have incorporated a third mechanism that reproduces those little shifts on everyone's opinion or social position, induced by individual circumstances and daily life experiences, that usually modify individuals' knowledge in a subtle but continuous way. This third mechanism is necessarily external, since these particular characteristics are different for each individual, and don't depend on any other parameter of the model. Notice that, at the mid-long time range, these slight but continuous shifts can change significantly the social distance among two individuals, separating two agents that were once very close in the lineal social space or, on the contrary, approximating them enough to favor the creation of a new link. Consequently, the accumulation of these microscopical changes can modify the whole macroscopical scenario, by disrupting both the distribution of agents' positions along the social space and their connectivity. Taking into account this disrupting effect over the whole system, closely similar to the concept of noise in physics and electronics, we have denoted this third mechanism of the dynamics as *social noise*.

These three mechanisms (rewiring, imitation and social noise) are integrated within the

co-evolutive dynamics of the model, consisting on the repetition of the following two steps:

1. Select an agent x at random and decide, with equal probability, whether to apply rewiring or imitation.
 - The rewiring consists on a redefinition of all links of node x using the expression in (1).
 - Imitation is implemented by selecting randomly a neighbor y of node x , and setting h_y equal to h_x .
2. Introduce the *social noise* by summing up a random quantity (obtained from a gaussian distribution with a 0 mean and fixed variance) to the h values of all agents in the population.

Fig. 1 illustrates this dynamics. At each time step, the system evolves following one of the two possible branches of the diagram (imitation plus *social noise*, or rewiring plus *social noise*) with the same probability.

After a certain number of time steps, the system reaches a *steady-state*. In our context, this means that both the topology and the distribution of individuals' social positions along the space remain stable. The concrete topology and distribution of social positions reached in each possible steady-state depend, as we will show in the next subsection, on the strength of the *social noise*.

Finally, two additional elements need to be included in our model to study social cohesion and its interplay with extremal changes on the social environment. On one side, it should be able to simulate different social temperatures (as stated in the previous

subsection). On the other hand, it has to include an observable to signal how these changes influence the social cohesiveness of the population.

The first requirement, introduction of changes on the social temperature, has been modeled as variations on the value of the b parameter (the one controlling the length scale of the social space). This solution can be justified as follows. When some kind of emergency strikes a population, social distances that separate individuals do not change, but the necessity to face the new critical scenario makes them less important than in a quiet situation. This temporal relativization of social distances is nothing else than a change on the length of the scale they are 'measured' with. Consequently, an appropriate way to introduce in our model the effect of emergencies and posterior relaxations of the conflict level, is to increase the value of b (making distances relatively smaller) and, after a relatively short number of time steps, reduce it back. b (making distances relatively smaller) and, after a relatively short number of time steps, reduce it back.

Regarding the monitoring of social cohesiveness, we have defined three different macroscopical observables, namely: the average degree $\langle k \rangle$ (average number of neighbors), the clustering coefficient (a weighted measurement of the number of triangles) and the number of disconnected components or independent groups G composing the whole network. While first and second parameters signal intra-group cohesion, the third one corresponds to inter-group cohesiveness. Note that, taken jointly, these three are good indicators of the social cohesiveness, since the more cohesive is a population, the higher are their average degree and clustering coefficients, and fewer separate groups it presents.

2.2. Effect of *social noise*

An important issue to deep in at this point, is the influence of the *social noise* over the evolution of the model. As said before, the strength of the social noise can determine the steady-state, that is, the stable configuration where the co-evolutionary model ends up. Since this noise is defined by a gaussian distribution with a fixed mean and variance, we center our attention on the unique parameter of the *social noise* that can be tuned: its magnitude.

In the context of our model, the magnitude corresponds to the average celerity of changes experimented by individuals' knowledge due to the *social noise*. Large amounts of *social noise* imply sudden changes of individual's social positions along the social space. On the contrary, low noises correspond to quite stable opinions.

Taking this into account, we can easily predict the behavior of the model for extremal values of the noise magnitude. On one side, too much *social noise* would result in a noise-dominated scenario, where agents would be almost completely isolated due to the difficulty to maintain links among them. On the other hand, if the noise was too less intensive it would exercise no significant effect over the dynamics, which would be controlled by the other two mechanisms (imitation and rewiring). Keeping this in mind, some questions arise: what are we to understand as "too weak" or "too strong" noise? And, how does the noise influence the dynamics for intermediate strength values between these limits?

In order to answer these questions, we have analyzed the influence of different noise magnitudes over the quantity of isolated components forming the network (G). In Figure 2, we present the evolution of G for a given set of initial conditions and different values of the noise strength. The results corroborate the predicted behaviors for extremal values of the

noise magnitude. Additionally, we observe that the case corresponding to an intermediate noise strength leads to steady-states with fewer isolated groups.

Such a surprising result can be related to the capacity of a moderate social noise to introduce heterogeneity within the different groups. This internal diversity favors the inter-group linkage without breaking them into isolated agents. Let’s explain this argument more accurately. When the social noise is weak, the combined action of imitation and rewiring leads the model to a steady-state where individuals tend to coincide in a unique h value (social position) and, therefore (because of the rewiring action), to conform a unique connected component. On the contrary, when the magnitude of the social noise is extremely high, differences between h values of agents (social distances among them) grow such quickly that cannot be counteracted by the imitation mechanism and, when those distances are too large to maintain links between neighbors, groups are progressively dissolved towards a completely disconnected scenario. In an intermediate situation, the noise intensity is high enough to maintain a wide variety of h values, but the differences introduced among these values are small enough to keep agents linked and, in some cases, to establish new links with agents belonging to other groups.

2.3. Experiment

In order to check the utility of our model as a tool to study the concept of social cohesion, we have conducted an experiment comprising two crisis cycles (sudden increases of the social temperature followed by longer reactionary periods). Each one of the crisis cycles has consisted on a short period (about 50000 time steps) of high social temperature (high values of b), followed by a fall to extremely low values of b (reproducing an habitual reactive behavior of populations after an emergency situation) and, finally, a progressive recovery

towards normality. The b values chosen to represent each period are 0.5 for 'normal' social temperature, 2.0 for highly conflictive situations and 0.25 - 0.35 for the reactionary intervals.

When looking at the behavior of the observables during the experiment, shown in figure 3, we observe two phenomena. First we notice that, for the same value of b , the social cohesiveness after each emergency situation is higher than before them. Second, we observe a memory effect on the cohesion of the system in the period between crises. Although the cohesiveness diminishes as a response to social temperature cooling, when the situation comes back to normality, the cohesiveness also recovers its "normal" value (that one corresponding to $b = 0.5$ just after the crisis).

The first result agrees with one of the observations made when we analyzed the three empirical cases, in the sense that the structure of the system changes during the conflict period. Moreover, it can be positively contrasted with observations of real social systems. When a population has been submitted to a stressing situation, it is quite usual to find higher levels of cohesion than before the crisis. In some sense, this phenomenon could be seen as a sort of *reminiscence* of the high rates of cohesion characterizing the emergency situation.

2.4. Analyzing mesoscopic and microscopic dynamical aspects of social cohesion

Up to this point, our model has revealed its capacity to reproduce how changes on the social temperature (which is a macroscopical variable related to the social environment) induces changes on the cohesiveness of a population of individuals (here measured in terms

of macroscopical observables).

Nevertheless, in the previous chapter we have argued that the analysis of the concept of social cohesion from a dynamical viewpoint demands a more complete scope of the problem, including also the behavior of different variables at meso and micro levels during the conflict period. In order to deep in this issue, we have studied how our model's dynamics modifies the distribution of agents' positions (h_i values) along the lineal social space and, consequently, how the social structure of the population is transformed.

In general, when plotting the distribution of agents' opinions in the social space at a steady-state (see Fig. 4 for two particular examples), we find that agents' positions are grouped around certain positions of the space, and that there are quite regular separations among these concentrations. Taking into account the dependence of the linkage probability on the social distance, we deduce that these concentrations of opinions in the social space correspond, structurally speaking, to groups of agents densely connected. Besides, the observed separations tend to a unique value that we have called *critical social distance* $d_c(h_i, h_j)$, which is the maximum social distance at which a link is possible or, in other words, is the distance to make the link probability close to 0:

$$d_c(h_i, h_j) = \lim_{r \rightarrow 0} d(h_i, h_j) = \lim_{r \rightarrow 0} b \sqrt[r]{\frac{1}{r(h_i, h_j)}} - 1 \approx \frac{b}{\sqrt[r]{r(h_i, h_j)}} \quad (2)$$

From this definition, it is straightforward that links are established only among agents separated by a distance smaller than $d_c(h_i, h_j)$. Moreover, the combined effect of imitation and rewiring makes that any agent located in a social position shorter than $d_c(h_i, h_j)$ from any group tend to link to that group, and that two groups tend to merge if they

are near enough from each other. Consequently, in the steady-state not only the distance among groups, but also their number and size, is related to the critical social distance. The larger the $d_c(h_i, h_j)$, the fewer separated groups and the larger the distance among them.

Furthermore, by taking a look to expression (2), we realize that *the critical social distance* depends on b . Since this variable controls the *social temperature* in our model, we can trace a causal path from variations on the social temperature to structural and knowledge changes experimented by the population during a crisis period. With this idea in mind, we can interpret the behavior of the cohesiveness during the experiment (shown in fig 3) in terms of reductions and increases of the critical distance, induced by changes on b (that is, the social temperature).

At the beginning of the experiment, before the first crisis, the critical distance is defined by the original b value (0.5). When the b value becomes 2.0, the critical distance also increases and, consequently, all agents come across other ones that were previously out of their range. Globally, this means that the population tend to reorganize into fewer but larger groups, whose opinions are separated each other by greater social distances. However, as this process is interrupted abruptly (due to the briefness of emergency situations), some agents are 'surprised' halfway between various groups. After a short transitory period, a new steady-state is reached. In this new stable scenario, agents conserve many neighbors of the period before the crisis and have incorporated new ones due to those agents bridging different groups after the emergency. Consequently, the resulting groups are larger than before the crisis and, because of their high internal connectivity, the average degree and the clustering coefficient also keep higher. This phenomenon is what we have previously called *reminiscence* of the crisis over the social cohesiveness.

At this point, agents are 'trapped' within their groups, their opinions are too much different from those of other groups to establish cross-links. Moreover, in this second stable period, the social noise plays a central role by opening very little internal discrepancies between members of the same group, that allow the creation of new groups when the social temperature gets 'colder' (b drops down to 0.25). Later, as the population recovers its 'normal' social temperature (and, therefore, the b value increases again), the critical distance grows up and little groups tend to merge and recover the stable configuration reached just after the crisis, presenting the second phenomenon pointed above, a memory effect. Finally, during the second cycle, the system presents the same behavior than in the first one: A higher cohesiveness than before and a memory effect.

3. CASE STUDY

Now that the model has been thoroughly detailed, it is possible to regain one of the examples outlined in the introduction and find out whether the model is relevant to them or not. In particular, we consider Stark's work on Hungarian economy, taking into account the amount of data it offers. As said, it analyzes the interactions of firms and parties across an entire epoch of economic and political transformation from 1987 to 2006 in a case where market-oriented enterprises and competitive political parties emerged.

Before reviewing the mentioned paper, it is necessary to confront its analysis with a brief description of the political context at the same period of time, in order to fully understand the model's descriptive power, since the aim is to match social unrest during

that epoch and economic behavior.

Soon after World War II, Hungarian parliament passed a new constitution of Hungary modeled after the 1936 constitution of the Soviet Union. The communist era endowed radical nationalization of the economy based on the Soviet model produced economic stagnation, lower standards of living and a deep malaise. However, the Hungarian Uprising in 1956 put a certain halt to Soviet-style politics and in the late 1960s a mixed economy was introduced in Hungary. Market prices and incentives gradually gained ground, and a partial privatization program was initiated. By the end of the 1980s almost half of economic activity was being generated by private business.

After 1989 Hungary's emerging market and parliamentary systems inherited a crisis-ridden economy with an enormous external debt and noncompetitive export sectors. The first free parliamentary election, held in May 1990, was won by center-right and liberal party Democratic Forum (MDF). Under Primer Minister József Antall, Hungary began to turn to the world market and restructured its foreign trade.

Péter Boross succeeded as Prime Minister after Antall died in December 1993. The Antall/Boross coalition governments achieved a reasonably well-functioning parliamentary democracy and laid the foundation for a free-market economy, but the massive worsening of living standards because of the free-market reforms led to a massive loss of support. Agriculture was drastically affected and declined by half. A large portion of the iron, steel, and engineering sectors, especially in northeastern Hungary, collapsed. Unemployment, previously nonexistent, rose to 14 percent in the early 1990s but declined after 1994.

By the mid-1990s the economy was again growing, but only moderately. Inflation peaked in 1991 and remained high, at more than 20 percent annually, until the second half of the decade. As a consequence of unavoidable austerity measures that included the elimination of many welfare institutions, most of the population lost its previous security; the number of people living below the subsistence level increased from 10 to about 30 percent of the population between 1988 and 1995.

The remarkable point after this historical outline is that, although there were negotiated, peaceful political openings, the democratization process in Hungary was not free of conflict. In fact, soon after 1990's first election, the center-right Hungarian government lost most of its popularity. Within six months of the national election of March 1990 their unpopularity was demonstrated in the overwhelming victory of the opposition parties in the local government elections creating a conflictive situation between local and national governments in many areas. Such discontentment endured the first half of the 1990s.

As it has been stated, both theoretically and by means of the simulation model, macro-political variables trigger conflict situations, and communities respond, through information exchange and mobilization at individual level, by increasing structural cohesion. Therefore, the conflictual environment in Hungary during the first years of democratization should match some evidence of cohesion growth. Stark's work on economy is not focused on social movements or protests, but still it presents some useful data that might endorse the point of view here assessed. With attention to temporal sequencing, their work measures cohesion in ownership networks. Fig. 5 presents the seven typical local network topographies derived by the cluster analysis: isolate, dyad, small star periphery, large star periphery, star center, cohesive cluster, and strongly cohesive group. The particular type of embeddedness

for any given firm, in any given year, is now categorized as one of the seven positions. The network history of a firm can now be represented as a sequence of topographies. Fig. 6 is an example of a firms history as it moves from one type of embeddedness to another. This firm starts as an isolate. After three years, it becomes the periphery of a small star. In 1992 the topography of the firms local network is a cohesive cluster, and after three years, these network ties are transformed into a strongly cohesive group. In 1998 the firm becomes a small star periphery again. At the end of the period, from 2000, the star shrinks into a dyad.

Now that the sequencing methodology is clear, the question whether social discontent correlates economy processes can be answered. Stark presents 1,696 such network histories-sequences of positions for each of the firms in their survey, grouped in terms of their sequence resemblance (such similar patterns are named *pathways*). Fig. 7 presents, for each of the pathways, the sequence of network positions that best represents firm histories in that pathway. As it indicates, cohesive recombinants match our hypothesis about cohesive patterns, and represent 18,2% of the firms, i.e. the second largest pathway, only outnumbered by isolates (one must take into account that small, family firms are not likely to be involved in ownership changes or joints). This pattern, and its significance in the whole data collection, can be interpreted as a delayed reaction to social non-economic cohesive processes at individual and community level.

4. CONCLUSION AND FUTURE RESEARCH

In this work we have developed a simple model as an analytic tool to explore a dynamic perspective of the concept of *social cohesion*, integrating the already-stated structural component (Moody & White 2003) with a cognitive, cultural one. Given a certain initial

scenario, the model evolves under the influence of the conflict level of the environment by redefining, simultaneously, the social structure and the knowledge or opinions (represented as positions in a social space) of a population of agents. We argue that, beyond static perspectives, the social cohesion of a population should be expressed in terms of these changes experimented both at structural and cognitive dimensions as a response to conflict increases.

By means of only three simple mechanisms, the dynamics of the model reproduces the behavior of real social populations under a highly conflictive situation. We have proven this in a threefold way. First we have studied how changes on a variable of the system representing the *social temperature* (degree of conflict) conditions the evolution of three observables that can be easily related to social cohesion (average degree, clustering coefficient and number of isolated components). Second, we have deepened in dynamic aspects of social cohesion by tracing the causal path among different topological levels: Changes on social temperature happen at an institutional level, influencing relationships among agents (microscopical level), and these changes at the individual level modify the size and composition of groups conforming the social population (mesoscopic or intermediate level). Finally, third, we have also compared the quantitative behavior of our model with empirical observations collected and analyzed in a previous work by (Stark & Vedres 2006).

Although having demonstrated its utility as a tool to analyze the concept of social cohesion, there are some aspects of the model that could be explored in order to make it more close to particular case studies. In the following, we point out two of these possible extensions of the model.

The initial conditions of our experiment, determined by a topology and a distribution of agents' opinions, can be defined in many different ways. In this case, we have chosen a simplistic initial scenario (synthetic social-like topologies and a uniform distribution of opinions) in order to show that, even starting with such simple conditions, our model is able to reproduce certain phenomena related to social cohesion and its dependence on variations on the social temperature. Nevertheless, each one of the two components of the initial scenario can be modified separately. For example, we could use a real social network (obtained by means of any sort of prospective tool from a real population) as the initial topology, but we could also start out the experiment with a distribution of opinions representing a scenario of preexistent coalitions or opinion groups.

Another possible extension of the model is related to the observables used to quantify the evolution of the social cohesion. Although the three structural observables used in this work are too much simple to represent population's cohesion separately, analyzing the evolution of their behaviors jointly has helped us to understand the dynamical processes taking place in the model. Nevertheless, for the sake of simpleness and clarity, it would be interesting to define a unique (necessarily more complex) structural observable, based on previous studies like (White & Harary 2001) and (Moody & White 2003). Furthermore, in accordance with the aim of this work of enriching the structural approach to social cohesion with a cultural component, it would also be interesting to define an observable related to the distribution of opinions in the social space (based on the largest social distance in the system, for instance).

5. ACKNOWLEDGEMENT

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REFERENCES

- Blau, Peter M. 1977. *Inequality and Heterogeneity*. New York: The Free Press of Macmillan Co.
- Blau, Peter M., and Joseph E. Schwartz. 1984. *Crosscutting Social Circles*. Orlando, FL: Academic Press
- Boguna, Marian, Romualdo Pastor-Satorras, Albert Diaz-Guilera, and Alex Arenas. 2004. "Models of social networks based on social distance attachment". *Phys. Rev. E*, 70 , 056122.
- Carley, Kathleen M. 1991. "A theory of group stability". *Am. Sociol. Rev.* 56:33154
- Coleman, James. 1990. *Foundations of Social Theory*. Cambridge, MA: Harvard University Press.
- DiMaggio, Paul. 1992. "Nadels paradox revisited: relational and cultural aspects of organizational structure". In *Networks and Organizations: Structure, Form, and Action*, edited by N. Nohria, and R.G. Eccles. Boston: Harvard Business School Press, pp.118-42.
- Durkheim, Emile. 1956. *The Division of Labor in Society*. The Free Press, New York.
- Fararo, Thomas J., and John Skvoretz. 1987. "Unification Research Programs: Integrating Two Structural Theories.", *American Journal of Sociology* 92 (1): 183- 1209.
- Forrest, Ray, and Ade Kearns. 2001. "Social cohesion, social capital and the neighbourhood". *Urban Studies* 38: 212543.
- Friedkin, Noah E. 2004. *Annual Review of Sociology* 30: 409-425.

- Gould, Roger V. 1991. "Multiple Networks and Mobilization in the Paris Commune, 1871". *American Sociological Review* 56 (7): 16-29.
- Gould, Roger V. 1993. "Collective Action and Network Structure". *American Sociological Review* 58 (2): 182-196.
- Gould, Roger V. 1995. *Insurgent Identities: Class, Community, and Protest in Paris from 1848 to the Commune*. Chicago: University of Chicago Press.
- Granovetter, Mark. 1973. "The Strength of Weak Ties." *American Journal of Sociology* 68: 1360-80.
- Granovetter, Mark. 1985. "Economic Action and Social Structure: The problem of Embeddedness". *American Journal of Sociology*, 91(3):481-510.
- Granovetter, Mark. 1992. "Problems of Explanation in Economic Sociology". In *Networks and Organizations: Structure, Form, Action.*, edited by N. Nohria and R. Eccles. Boston: Harvard Business School Press.
- Hirsch, Eric L. 1990. "Sacrifice for the Cause: Group Processes, Recruitment, and Commitment in a Student Social Movement". *American Sociological Review* 55 (2): 243-254.
- Holme, Peter, and Mark E.J Newman. 2006. "Nonequilibrium phase transition in the coevolution of networks and opinions". *Phys. Rev. E* 74, 056108.
- Kawachi, Ichiro, and Bruce P. Kennedy. 1997. "Health and social cohesion: why care about income inequality?" *British Medical Journal* 314: 1037-1040.
- Kearns, Ade, and Ray Forrest. 2000. "Social Cohesion and Multilevel Urban Governance". *Urban Studies* 37 (56): 9951017.

- Lazer, David. 2001. "The co-evolution of individual and network". *J. Math. Sociol* 25:69108
- Marsili, Matteo, Fernando Vega-Redondo, and Frantisek Slanina. 2004. "The rise and fall of a networked society: A formal model". *Proc. Nat. Acad. Sci.* 101: 1439-1442.
- McPherson, Miller, Lynn Smith-Lovin, and James M. Cook. 2001. "Birds of a feather: Homophily in Social Networks". *Annu. Rev. Sociol.* 27: 415-44.
- Moody, James, and Douglas R. White. 2003. "Structural Cohesion and Embeddedness: A Hierarchical Concept of Social Groups". *American Sociological Review* 68 (1): 103-127.
- Murphy, Robert F. 1957. "Intergroup Hostility and Social Cohesion". *American Anthropologist* 59 (6): 1018-1035.
- Nadel, S.F. 1957. *Theory of Social Structure*. London: Cohen and West.
- Polanyi, Karl. 1944. *The Great Transformation*. New York: Rinehart and Co.
- Putnam, Robert. 1993. *Making Democracy Work. Civic Traditions in Modern Italy*. Princeton: Princeton University Press.
- Putnam, Robert. 1995. "Bowling Alone: America's Declining Social Capital". *Journal of Democracy* 6 (1): 65-78.
- Putnam, Robert. 2001. "Social Capital: Measurement and Consequences". *Isuma-Canadian Journal of Policy Research* 2 (1): 41-51.
- Radcliffe-Brown, A.R. 1940. "On Social Structure". In *Social Networks; a Developing Paradigm*, edited by Samuel Leinhardt in 1977. New York: Academic Press. pp. 221-232.

- Room, Graham (ed.). 1995. *Beyond the Threshold: The Measurement and Analysis of Social Exclusion Bristol*. The Policy Press.
- Snijders, Tom A.B. 2005. "Models for Longitudinal Network Data". In *Models and methods in social network analysis*, edited by P. Carrington, J. Scott, and S. Wasserman. New York: Cambridge University Press.
- . Snijders, Tom A.B.; Christian E.G Steglich, and Michael Pearson. 2006. *Dynamic Networks and Behavior: Separating Selection from Influence*. Groningen: RuG.2007.
- Snow, David A., E. Burke Rochford, S.K. Worden, and Robert D. Benford. 1986. "Frame Alignment Processes, Micromobilization, and Movement Participation". *American Sociological Review* 51 (4): 464-481.
- David Stark and Barzs Vedres. 2006. "Social Times of Network Spaces: Network Sequences and Foreign Investment in Hungary". *American Journal of Sociology* 111 (5): 1367-1411
- Wasserman, Stanley, and Katherine Faust. 1994. *Social Network Analysis: Methods and Applications*. Cambridge: Cambridge University.
- Wasserman, S., and G.L. Robins. 2005. "An Introduction to Random Graphs, Dependence Graphs, and p^* ". In *Models and Methods in Social Network Analysis* (pp. 148-161), edited by P. Carrington, J. Scott, and S. Wasserman. New York: Cambridge University Press
- Wellman, Barry, and Barry Leighton. 1979. *Urban Affairs Quarterly*, 14(3): 363-390.
- Wellman, Barry, Janet W. Salaff, Dimitrina Dimitrova, Laura Garton, Milena Gulia, and Caroline Haythornthwaite. 1996. "Computer Networks as Social Networks:

- Collaborative work, Telework and Virtual Community”. *Annual Review of Sociology* 22: 213-238.
- White, Douglas R., and Frank Harary. 2001. ”The cohesiveness of blocks in Social Networks: Node connectivity and Conditional Density”. *Sociological Methodology*, 31: 305-359.
- White, Douglas R., Jason Owen-Smith, James Moody, and Walter W. Powel. 2004. ”Networks, Fields and Organizations: Micro-Dynamics, Scale and Cohesive Embeddings”. *Computational and Mathematical Organization Theory*, 10 (1): 95-117.
- Wilkinson, Richard G. 1996. *Unhealthy Societies: The Afflictions of Inequality*. London: Routledge.
- Wolfe, David A. 2002. ”Social Capital and Cluster Development in Learning Regions” in *Knowledge, Clusters and Learning Regions*, edited by J. Adam Holbrook and David A. Wolfe. Kingston: School of Policy Studies, Queen’s University.

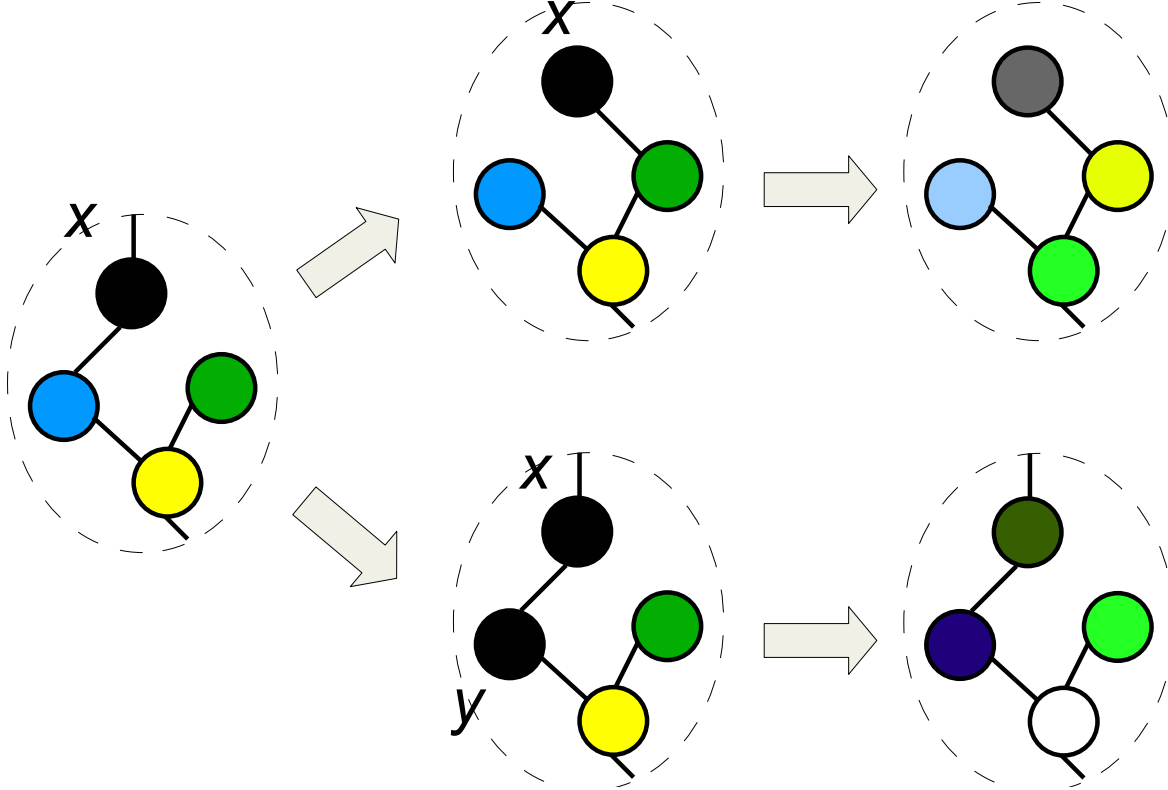


Fig. 1.— An illustration of our co-evolutive dynamics, where colors indicate the h value of each individual. At each time step, the system evolves following one of the two branches. The upper branch correspond to a rewiring (of x 's links) plus a shift of all positions, and the lower one to imitation (y imitates x) plus position shifts.

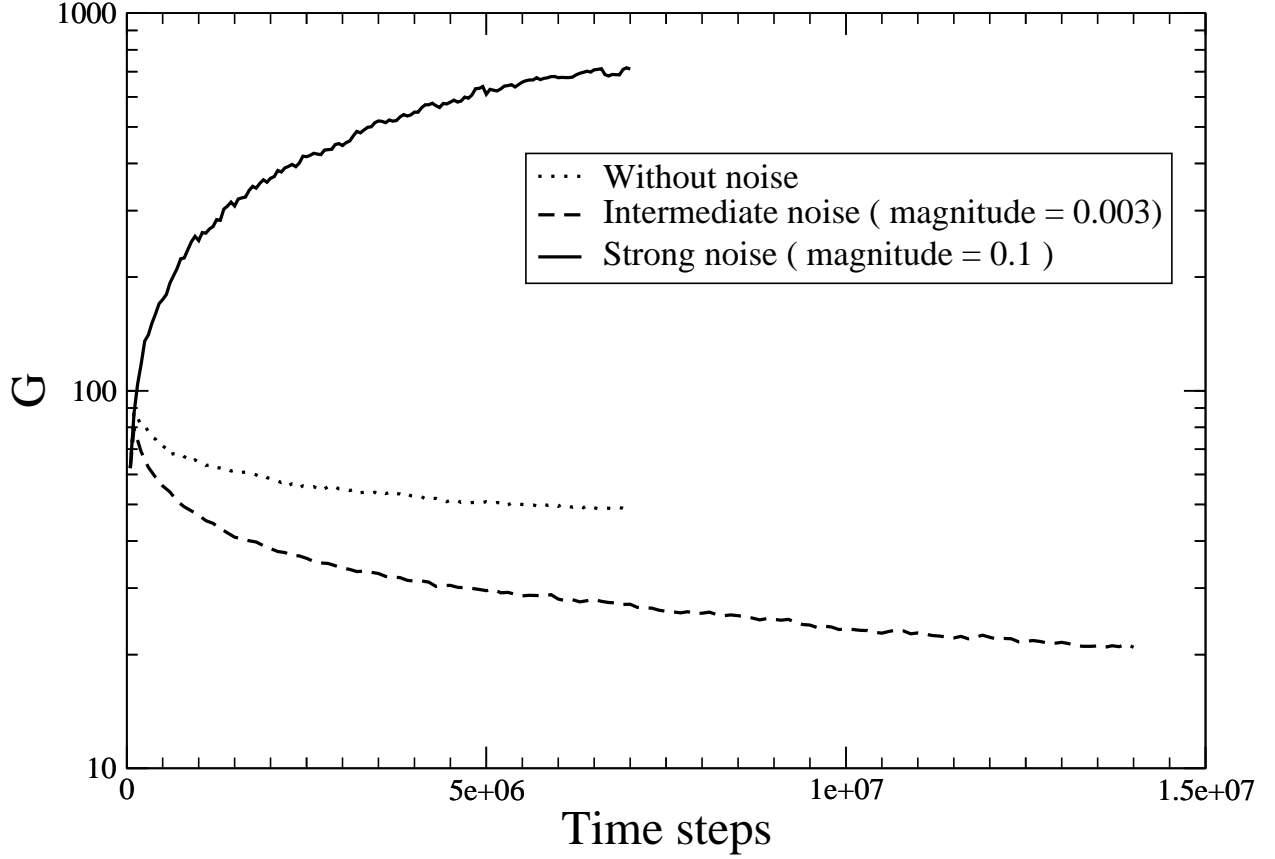


Fig. 2.— Influence of noise magnitude over model dynamics. Evolution of the number of separated components of the network (G), for three different values of the noise strength (representative of strong, intermediate and weak noise strength). The case without noise is also shown, for comparative purposes. Results have been averaged among 25 independent realizations.

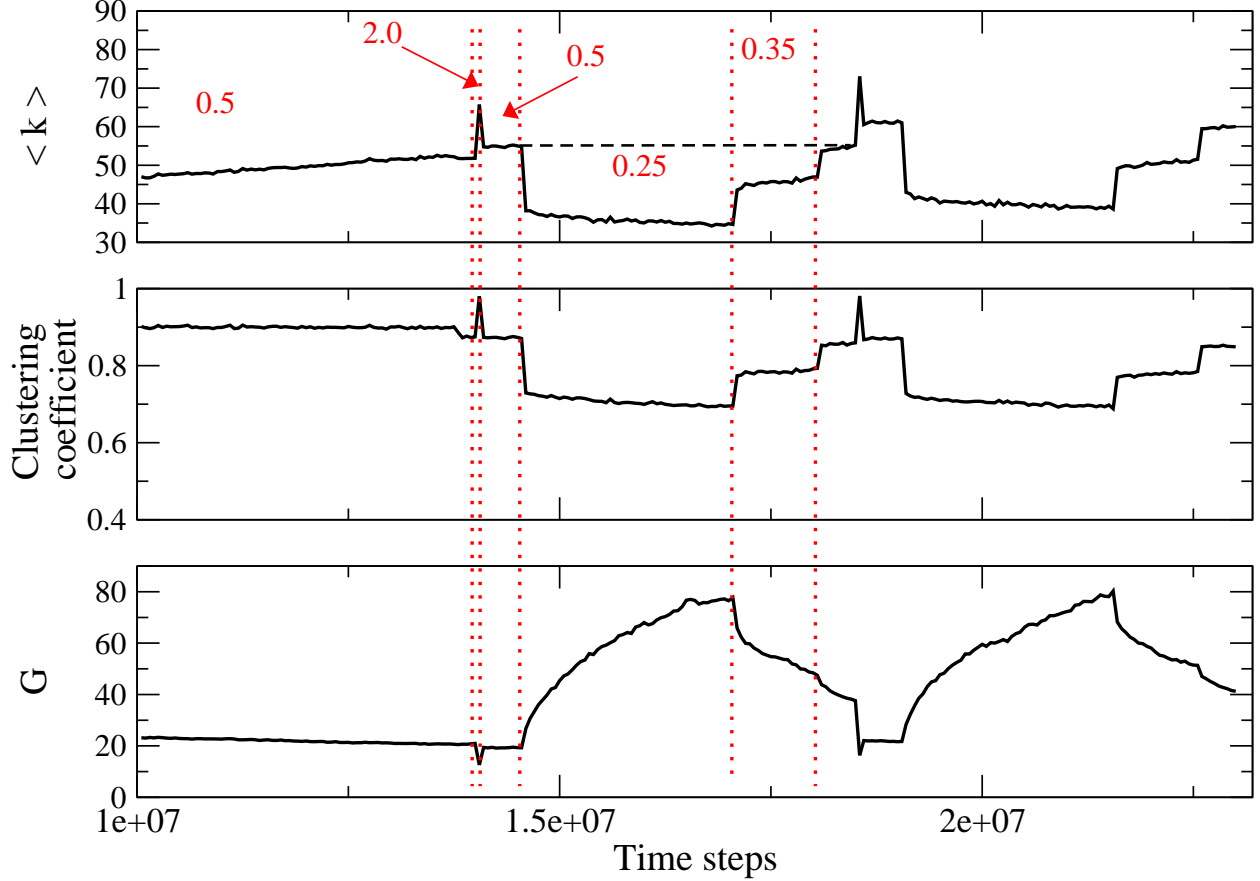


Fig. 3.— Evolution of social cohesiveness of a population of $N = 1000$ agents during the experiment. Vertical dashed lines in red indicate regions delimited by their b value, which are indicated also in red. The other main parameters of the model, α and the noise magnitude, were set to 6 and 0.003, respectively. Two important phenomena are observed: An increase on the average cohesion after each crisis, and a memory effect in the period between crises (represented here by a horizontal dashed line in black). Results were obtained by averaging 25 independent realizations.

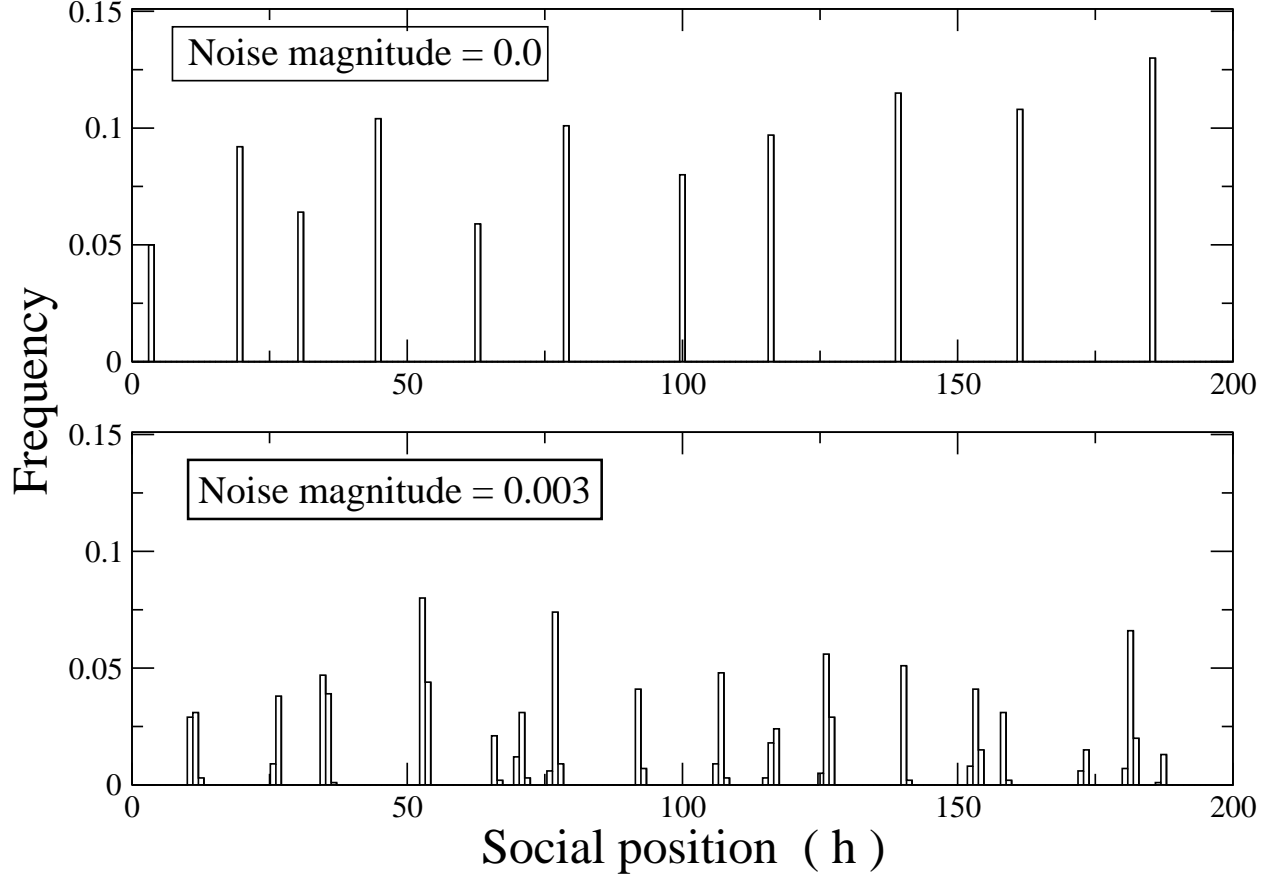





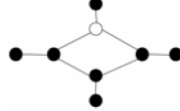
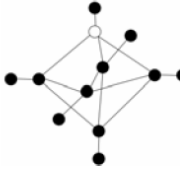


Fig. 4.— Distribution of agents' positions along the lineal social space, in a steady-state, without social noise (top) and with a social noise of magnitude 0.003. Although both cases present quite regular separations between groups (see text for an explanation), the internal distribution of each group differs. In the bottom case, we appreciate the heterogeneity within groups introduced by the social noise.

Local network positions.				
Network position	N	Percentage of non-isolate	Means of ego network statistics	Graph illustration ^a
I. Isolate	12 378	-	Size: 0.00 Alters' size: 0.00 Cohesion: 0.00 Alters' cohesion: 0.00	
D. Dyad member	1 260	22.12%	Size: 1.00 Alters' size: 1.00 Cohesion: 0.00 Alters' cohesion: 0.00	
P. Small star periphery	1 985	34.86%	Size: 1.22 Alters' size: 3.34 Cohesion: 0.00 Alters' cohesion: 0.00	
L. Large star periphery	280	4.92%	Size: 1.05 Alters' size: 12.10 Cohesion: 0.00 Alters' cohesion: 0.00	
S. Star center	543	9.53%	Size: 3.37 Alters' size: 1.35 Cohesion: 0.00 Alters' cohesion: 0.00	
C. Cohesive cluster member	899	15.79%	Size: 2.84 Alters' size: 6.82 Cohesion: 0.46 Alters' cohesion: 1.20	
G Strongly cohesive group member	728	12.78%	Size: 2.71 Alters' size: 9.91 Cohesion: 2.40 Alters' cohesion: 8.55	
Total	18 073	100.00%		

Note: a: White node indicates local network position in graph illustrations.

Fig. 5.— The seven typical local network topographies derived by the cluster analysis: isolate, dyad, small star periphery, large star periphery, star center, cohesive cluster, and

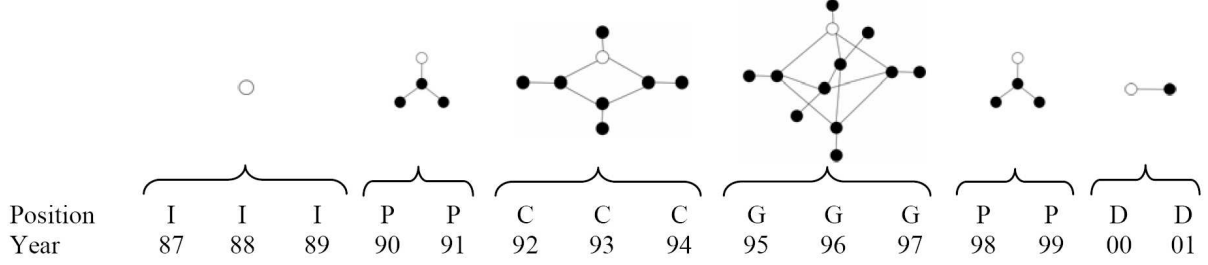


Fig. 6.— One particular example of firms history along the period studied. (Stark & Vedres 2006).

PATHWAYS' TYPICAL SEQUENCES OF NETWORK POSITIONS

PATHWAYS	N	YEAR ^a															SHARE IN CATEGORIES OF CAPITAL IN 2001	
		1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	All	Networked Foreign
Star-periphery recombinants:																		
1	34	I	I	I	S	S	S	S	S	S	S	S	S	S	S	S	7.1	1.4
2	106				P	P	P	P	P	P	P	P	P	P	P	P	3.8	3.0
Cohesive recombinants:																		
3	70		I	I	P*	P	C	C*	C	C	C	C	C	P	P	P	18.2	36.1
4	44			C	C	C	G	G	G	G*	G	C	C	C	C	C	4.9	12.2
5	65			C	C	C	G	G	G	G	G	G*	G	I	I	I	3.6	0.6
6	56	I	I	I	I	I	I	I	I	L	L	C	C	G	G	G	7.0	6.7
Start-ups:																		
7	63			P	P*	P	P	P	P	P	I	I	I	I	I	I	3.4	0.0
8	97				D	D*	D	D*	I	I	I*	I	I	I	I	I	4.2	0.3
9	70				P*	P	P	P	P	D	D*	D	D	D	D	D	3.9	8.6
Second-wave networks:																		
10	136	I	I	I	I	I	I	I	I	D*	D	D	D	P	P	P*	9.1	21.6
11	101											D*	D*	P	P	P	3.3	8.7
Isolates:																		
12	854						I	I	I	I	I	I*	I	I	I	I	30.7	0.0
Total	1,696																100.0	100.0

NOTE.—I = isolate, D = dyad member, P = star periphery, L = large star periphery, S = star center, C = cohesive cluster member, G = strongly cohesive group member.

^a Cells indicate network positions from fig. 2.

* Surges in foreign investment when new foreign capital amounted to at least 20% of the total capitalization of the pathway in that year.

Fig. 7.— Sequences of network positions that best represents firm histories in each pathway. Reference to Table 2 in the foot-note corresponds to 6in this paper. (Stark & Vedres 2006).